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Genetic evaluation of US dairy cattle in the presence of preferential treatment

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Genetic evaluation of U.S. dairy cattle in the presence of preferential treatment

by

Melvin Thomas Kuhn

A dissertation submitted to the graduate faculty

in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

Major: Animal Breeding

Major Professor: Albert E. Freeman

Iowa State University

Ames, Iowa

1998

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For the Major Program

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GENERAL INTRODUCTION

Selection is the primary tool used to bring about genetic progress in livestock populations. The amount or rate of change brought about by selection, called response, is a function of four factors: intensity, accuracy, additive genetic variance, and generation interval. Intensity of selection is a function of proportion of animals in the population used as parents. As intensity increases (proportion kept decreases), response to selection increases. Thus, it is typical for a breeding program to use as few animals as physiologically possible for reproduction.

Since breeding (genetic) value cannot be observed directly, selection must be based on some sort of genetic evaluation, an estimate of animals' breeding values. One of the, if not the, primary goal(s) in the estimation of breeding value is maximization of accuracy. For most livestock populations, selection is based on the best linear unbiased predictor (**BLUP**) of breeding value, using a linear model called an animal model. The fundamental feature of any animal model is a random "animal effect," which is the animal's breeding value, and whose variance-covariance matrix is $A\sigma_a^2$, where A is a matrix containing all known additive relationships. Thus, by also including known environmental (non-genetic) effects, the BLUP of breeding value, based on an animal model, accomplishes two key aspects to genetic evaluation: correction for environmental effects and utilization of all known relationships.

For U.S. dairy cattle, genetic evaluations are computed by USDA . In July 1989, USDA switched from the modified contemporary comparison to BLUP based on an animal model for calculating the national evaluations, called predicted transmitting abilities (**PTA**). One key feature, as far as this research is concerned, is that the records for these genetic evaluations come from privately owned herds from across the U.S. Any producer who so desires can enroll in the record keeping system provided by the Dairy Herd Improvement Association (DHIA). DHIA then supplies USDA with the data for computing genetic evaluations.

In the U.S. dairy cattle industry, virtually all selection is done by the artificial insemination (**AI**) organizations. Two-stage selection is practiced. The first stage involves selecting sires and dams of potential new AI sires. Second stage selection involves choosing among the bulls produced from the matings in first stage selection and is based, primarily, on the performance of the daughters of the new bulls. About one of eight bulls produced in first stage selection will be kept in the second stage of selection.

In first stage selection, the sires of new sires are the best and most popular of the "current" AI sires. The dams typically come from the commercial cow population and are owned by private producers. Intensity of selection on these dams is quite high. Out of approximately 2.5 million cows, only about 1100 are chosen annually as dams of new sires.

There is motivation, both financial and prestige, for an owner to have one of their cows selected as a bull dam. This incentive has led, both AI personnel and academians, to the firm belief that preferential treatment (**PT**) is practiced in the U.S. dairy cattle population, whereby a producer will treat one cow better than others in the herd in an attempt to increase her production and, thus, her chances of being chosen as a bull dam. If an unbiased source of information was available, upon which selection could be based, then PT would not be a problem. It was not known, however, how a PT effect would be partitioned among the various terms in the USDA animal model.

The first goal of this study, therefore, was to determine the bias in female PTAs, caused by PT. The second goal was to determine biases in sire PTAs when their daughters receive PT. Biases found were large. Thus, the final goal was to investigate possible approaches to correcting for PT in genetic evaluation.

Dissertation Organization

This dissertation is written in paper format. Following this introduction are three papers, each addressing one of the three goals stated. General conclusions are included after the third paper.

POTENTIAL BIASES IN FEMALE PREDICTED TRANSMITTING ABILITIES CAUSED BY PREFERENTIAL TREATMENT[1]

A paper published in the Journal of Dairy Science

M. T. Kuhn, P. J. Boettcher, and A. E. Freeman

ABSTRACT

Data were simulated according to the USDA animal model to determine potential biases in female PTA caused by preferential treatment. Ten scenarios for preferential treatment were investigated. Scenarios were defined according to three factors: number of records for the cows receiving preferential treatment, whether all or only second and later records received preferential treatment, and whether preferential treatment was added only to records of cows selected for preferential treatment or to selected cows and their relatives (dam or dam and maternal sibs). Three levels of preferential treatment were studied. Each level was studied separately to allow straightforward determination of whether bias increased linearly as level of preferential treatment increased.

Within each scenario, bias increased linearly as level of preferential treatment increased, but magnitude of bias varied across scenarios. As a proportion of preferential treatment effect, bias in PTA ranged from .06 to .39. Affording preferential treatment to relatives increased bias more than increasing the number of lactations with preferential treatment.

INTRODUCTION

Preferential treatment (PT) can be described as any management practice that increases production and is applied to one or several cows, but not to their contemporaries. Some of these practices might be separate housing, better or more feed, greater number of days open relative to contemporaries, or longer milking intervals on test day for the cow receiving preferential treatment.

Of course, some PT may occur inadvertently. A standard management practice, for example, is to feed cows according to their level of production. Presumably, the primary motivation for intentional PT, however, would be to enhance the likelihood that a cow will be chosen as a bull-dam or sold at an increased price.

Popular opinion is that intentional PT occurs among U.S. dairy cattle. Historically, a primary argument for the existence of PT has been that the cow index of bull-dams failed to predict sons' PD as accurately as theory dictated (12). Several studies (6, 10, 13) found that the cow index of bull-dams predicted son PD better when the cow index was based on first records only than when it was based on second and later records or when it was computed from all records. The typical conclusion from this result was that PT was practiced in second and later parities and was prompted by an outstanding first record.

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[1] Journal Paper Number J-15545 of the Iowa Agriculture and Home Economics Experiment Station, Ames. Project Number 3141.

Powell and Norman (8) investigated how well cow index predicted daughter production. They assumed that PT had occurred among dams with high cow indexes and they therefore expected cow index to overpredict daughter production for those dams. However, they found that cow index, for dams with high cow indexes, actually underpredicted daughter production. Their conclusion was that PT had occurred among high cow index dams but that PT had also been applied to the daughters.

Thus, indirect evidence supports the idea that PT occurs among elite U.S. dairy cows and that cow indexes could be biased by PT. Animal model predictions of genetic merit may also be biased by PT. Ferris (2) reported that parent average predicted transmitting ability (**PTA**) overpredicted sons' daughter-yield deviation by 13 kg. Results of Samuelson and Pearson (11) implied that dam PTA, from animal model evaluations, predicted sons' first evaluation more accurately than cow index did, but still less accurately than theoretically expected. These results (2, 11) suggest that animal model genetic evaluations may also be biased by PT. The objective of this research was to determine to what extent PT can bias female genetic evaluations for milk yield computed from the USDA animal model (15) used for genetic evaluation of U.S. dairy cattle. The complete partitioning of the PT effect, across all model terms, was also examined.

MATERIALS AND METHODS

General Approach

To evaluate the objective of this study, the use of simulated data held some definite advantages over use of actual data; the true properties of simulated data are known and could be easily manipulated. Hence, the general approach to addressing the objective included the following: 1) data with no PT effects were simulated; 2) unbiased PTA based on non-PT records were computed; 3) cows to receive PT were selected from the simulated population; 4) PT effects were added to the record(s) of selected cows; 5) biased PTA based on PT records were computed; and 6) bias was estimated as: biased PTA - unbiased PTA.

Simulation of Data

Model for Simulation of Records. The model for simulation of records was the USDA animal model used to compute national genetic evaluations for dairy cattle (15). The model equation can be written as

$$y = M + PE + S \times H + A + e \quad [1]$$

where y is a phenotypic milk record; M is a management group effect; PE is a permanent environmental effect; S x H is a sire by herd interaction effect; A is animal effect; and e is a residual effect. Definition of management groups was the same as that used by the USDA for computation of the national evaluations (16).

Management group effects (M) were generated as:

$$M = H + Y + S + P + R + HYSPR \quad [2]$$

where H, Y, S, P, and R are herd, year of calving, season of calving, parity, and registration effects, respectively, and HYSPR is a herd-year-season-parity-registration interaction effect that is unique to a particular management group. Numerical values used in simulation are summarized in Table 1 for each effect. The relative frequencies and effects of season were taken from Miller (4) and registration effects from Powell and Norman (9). Herd, year, and HYSPR effects were generated as normal random variables with expectations of zero and variances given in (Table 1).

To generate the components of records, a total phenotypic variance of (1518 kg)^2 was used. This variance was derived by averaging the within-parity variances reported by Hansen et al. (3) and then adding an additional variance of (250 kg)^2 for parity effects. This total variance was partitioned among record components, as summarized in Table 1. Forty percent of the total variance was attributed to management effects, which was consistent with the proportion of total variance attributed to herd-year-season effects by Hansen et al. (3). The remaining 60% of variance was apportioned among random components (Table 1) according to the variance ratios currently used by USDA in computing the national PTA (16). All random effects were generated as normal random variables. Permanent environmental, sire by herd interaction, and residual effects all had expectations of zero. Expectation of breeding value was zero for all base animals (animals with unknown parents), while expected breeding value for nonbase animals (animals with known parents) was parent average breeding value.

TABLE 1. Parameters used for simulation.

Effects and relative frequencies for season of calving, registry status, and parity

	Season						Registry[1]		Parity[2]	
	Jan-Fan	Mar-Apr	May-June	July-Aug	Sep-Oct	Nov-Dec	G	R	1	≥2
Effect, kg	179	68	-158	-319	43	187	-68	68	-250	250
Relative Frequency	.16	.11	.11	.23	.23	.16	.55	.45	NA	NA

Partitioning of total variance among record components[3]

	Management effects[4]				Random effects[4]			
	Herd	Year	S, P, R	HYSPR	PE	S x H	A	e
Total Variance, %	22	6	11	1	9.6	8.4	15	27
SD, kg	712	372	503	152	470	440	588	789

[1] G = grade, R = registered.
[2] NA = Not applicable.
[3] Total variance for management effects was 40% or (960 kg)^2; total variance for random effects was 60% or (1176 kg)^2; total variance was (1518 kg)^2.
[3] S, P, R = season, parity, registry; HYSPR = herd, year, season, parity, registry interaction; PE = permanent environmental; S x H = sire by herd interaction; A = animal; e = error.

Structure and Characteristics of Simulated Populations. The simulation program generated data year by year. To establish a sufficient relationship structure in the population, 20 yr of data were generated in each run of the simulation program. By yr 20, all animals had at least three, and 98% had at least four, generations of known ancestors.

Population size was 30,000 or 50,130 milking cows per year and depended on the "scenario" for PT (defined in next section). The herd sizes and herd size frequencies used for simulation (Table 2) were based on herd statistics reported by Wiggans and Ernst (14). Ratio of registered to grade cows (Table 1) was based on random samplings of the Animal Improvement Programs Laboratory data (1, 7).

TABLE 2. Herd sizes and frequencies used in the simulation of data.

Herd size	18	38	62	85	120	170	240	343	446	600	856	1185	
Frequency													Total
Population[1]	23	138	105	46	36	12	10	3	2	2	1	1	379
Population[2]	39	234	179	79	60	19	15	6	3	4	2	1	641

[1] Herd size frequencies when population size was 30,000 milking cows per year.
[2] Herd size frequencies when population size was 50,130 milking cows per year.

Culling was at random for cows and rates were .22, .26, .29, .34, and 1.0 for parities 1 through 5, respectively (based on (7) but with no lactations beyond 5th). Records beyond 5th are not used in genetic evaluation (15) and are relatively rare in the actual population (7). Sires of all nonbase animals were generated as AI sires and two-stage sire selection was simulated. Ten (or 16) active and 21 (or 35) progeny test sires (population size 30,000 or 50,130) were available for use each year.

PT Models

Scenarios for PT. The scenarios for PT used in this study were defined according to factors expected to affect the level of bias in PTA. The scenarios were then studied separately to determine whether biases were different in the different scenarios.

Three factors were considered in the definition of scenarios: 1) whether PT was to be applied only to the animal itself or, as suggested by Powell and Norman (8), to a cow and her relatives (dam or dam and sibs); 2) whether PT was to be applied to all records of cows selected to receive PT or to second and later records only, as suggested by several authors (6, 10, 13); and 3) total number of records for cows receiving PT.

Ten scenarios were used as defined in Table 3. The first five scenarios involved PT only on the animal itself. Scenarios 1 and 2 involved PT on second and later lactations only; cows had two (scenario 1) or three (scenario 2) lactations. Scenarios 3, 4, and 5 involved PT on all records of the cow; cows had 1, 2, or 3 records, respectively.

Scenarios 6 through 10 involved PT on all records of cows selected for PT and all records of certain relatives. The cows used in scenarios 6, 7, and 8 were also used in scenarios 3, 4, and 5. However, in scenarios 6, 7, and 8 PT was also applied to all records on the dams of those cows. Scenarios 9 and 10 were "flush" scenarios. In scenario 9, 23 flush dams (cows with multiple female progeny per year) were selected from the simulated population and two sets of five daughters were generated for each flush dam. Daughters from the same flush dam, but in different daughter groups, had different sires. Thus, daughters from the same dam were either full-sibs (if they were in same daughter group) or maternal half-sibs (if they were in different daughter groups). Scenario 10 was comparable with scenario 9, except that 4 sets of 5 daughters were generated on each of 12 flush dams. In scenarios 9 and 10, PT was applied to flush daughters and dams.

TABLE 3. Scenarios for preferential treatment (PT)[1].

I. PT only on records of animals selected to receive PT

- a) PT on second and later records only
  1. Cows selected for PT had two records.
  2. Cows selected for PT had three records.
- b) PT on all records
  3. Cows selected for PT had one record.
  4. Cows selected for PT had two records.
  5. Cows selected for PT had three records.

II. PT on all records of cows selected for PT and on all records of certain relatives

- a) PT on cow and her dam
  6. Cows selected for PT had one record.
  7. Cows selected for PT had two records.
  8. Cows selected for PT had three records.
- b) PT on flush dam and flush daughters
  9. Ten daughters for each flush dam.
  10. Twenty daughters for each flush dam.

[1] Arabic numbers indicate scenario number.

Selection of Cows to Receive PT. Selection of cows to receive PT was restricted to the latest years possible. In scenario 3, for example, where cows needed only one record, selection was restricted to cows that first calved in yr 20. In scenario 4, where cows needed two records, selection was restricted to cows that first calved in year 19.

After restriction to cows in the latest possible years, there were typically 9000 to 10000 cows available for PT. The algorithm for selection of cows to receive PT was to randomly select 150 cows (scenarios 1 through 8) or, 23 or 12 cows (to be used as flush dams for scenarios 9 and 10), from among the "best" five percent of all available cows.

Criterion for best was magnitude of first record for scenarios 1 and 2 and parent average PTA in scenarios 3, 4, and 5. The same cows were used in scenarios 6, 7, and 8, as in scenarios 3, 4, and 5 and, thus, the same criterion applied in those scenarios. In the flush scenarios, parent average PTA of the flush dam was used as the criterion for selection.

Population size was 30,000 milking cows per year in scenarios 1 through 8 and 50,130 cows in the two flush scenarios. Thus, ratio of number of cows receiving PT to population size was approximately .005 in all scenarios. For scenarios 1 through 8, population size of 30,000 milking cows per year was considered adequately large and required less computing time than the 50,130 cow populations. Population size was increased for scenarios 9 and 10 to allow for selecting more flush dams while at the same time maintaining the same proportion of cows receiving PT.

Levels of PT and Estimation of Bias

To determine whether bias in PTA increased linearly as level of PT increased, three levels of PT (227, 907, and 2270 kg) were investigated. Table 4 outlines the design used to estimate bias. Consider row 1 of Table 4 which corresponded to estimation of bias for scenario i when level of PT was 227 kg. The procedure was to obtain 4 statistically independent estimates of bias ($\bar{X}_{i11.}$, $\bar{X}_{i12.}$, $\bar{X}_{i11.}$, $\bar{X}_{i12.}$) and then compute the simple average of the 4 replicate means ($\bar{X}_{i1..}$). An estimate of the standard error of $\bar{X}_{i1..}$ was computed as the square root of the variance among the replicate means. The overall statistics (labeled as $\bar{X}_{ij..}$ and SE in Table 4) were then used as the statistics for inference. For each replicate, bias ($\bar{X}_{ijk.}$) was computed as biased PTA minus unbiased PTA, averaged across all cows that received PT. PT effects were introduced by simply adding the PT level under study to tne phenotypic records which were to receive PT. The same procedure was used to estimate bias for each scenario by PT level combination.

TABLE 4. Outline of design used for estimation of bias.

Scenario	PT[1] Level (kg)	Replicate[2] 1	2	3	4	Overall[3] $\bar{X}_{ij..}$	SE
i	227	$\bar{X}_{i11.}$	$\bar{X}_{i12.}$	$\bar{X}_{i13.}$	$\bar{X}_{i14.}$	$\bar{X}_{i1..}$	s_{i1}
	907	$\bar{X}_{i21.}$	$\bar{X}_{i22.}$	$\bar{X}_{i23.}$	$\bar{X}_{i24.}$	$\bar{X}_{i2..}$	s_{i2}
	2270	$\bar{X}_{i31.}$	$\bar{X}_{i32.}$	$\bar{X}_{i33.}$	$\bar{X}_{i34.}$	$\bar{X}_{i3..}$	s_{i3}

[1] Preferential treatment.

[2] $\bar{X}_{ijk.}$ = Mean bias, across all cows selected for PT, in scenario i (i = 1, 2, ..., 10), at PT level j (j = 1, 2, 3) for replicate k (k = 1, 2, 3, 4);

$$= \sum_{m=1}^{NPT} (bPTA_{ijkm} - uPTA_{ijkm}) / NPT, \text{ where}$$

NPT = number of cows receiving PT = 150 in scenarios 1 through 8;
= 23 and 12 for calculation of bias on flush dams in scenarios 9 and 10, respectively;
= 230 and 240 for calculation of bias on flush daughters in scenarios 9 and 10, respectively;
$bPTA_{ijkm}$ = biased PTA based on PT records for cow m, in scenario i, at PT level j, in replicate k;
$uPTA_{ijkm}$ = unbiased PTA based on non-PT records for cow m, in scenario i, at PT level j, in replicate k.

[3] $\bar{X}_{ij..}$ = Simple average of the four replicate means for the ijth scenario by PT level combination; s_{ij} = standard error of $\bar{X}_{ij..}$

The ratio of overall mean bias ($\bar{X}_{ij.}$ in Table 4) divided by level of PT was also calculated for each scenario by level of PT combination. If bias increased linearly as level of PT increased, then the ratio of bias to PT level would correspond to the slope of the line representing that linear relationship. Thus, within scenarios, equality of these ratios indicated a linear increase in bias as level of PT increased within the range of PT effects studied. Furthermore, each column, labeled as replicate in Table 4, corresponded to one simulated population and so each cow selected for PT was used for each of the 3 levels of PT. Therefore, there was no between cow error among the overall (row) means of Table 4.

One implication of studying the levels of PT separately was that the PT effects were modeled as constants rather than random variables. This was done to allow straightforward determination of whether bias in PTA increased linearly as level of PT increased. However, given that PT effects do not likely behave as constants in the actual population, some question remained as to whether ratios of bias to PT would be the same if PT effects were modeled as random variables rather than constants. To address this concern, the three levels of PT were also applied randomly to cows in the relative frequencies of .2 (227 kg), .45 (907 kg), and .35 (2207 kg) for each scenario. When cows had more than record which was to receive PT, the same PT level was used for each record. Bias was then estimated as described before and ratio of mean bias to mean PT effect was computed.

Computation of PTA

The PTA were computed as one-half times actual animal solutions from the USDA animal model, equation [1]. Management effects were assigned to records, in the simulation of data, according to equation [2] regardless of group size. If, however, group size was less than five, groups were combined according to the algorithm utilized by the USDA (16). Animal model solutions were obtained using Misztal's JAA program (5).

Data included all records on all nonbase cows. Records on base cows were not included in the calculation of solutions because their sires were unknown (15). The relationship matrix was complete, including base animals. For the 30,000 cow populations, there were 210,829 cows, 367 sires, and 174,245 PE solutions (equal to number of nonbase cows). For the 50,130 cow populations, there were 352,280 cows, 611 sires, and 291,148 PE solutions.

RESULTS AND DISCUSSION

Results (Tables 5 and 6) clearly indicated potential for substantial bias in female PTA for cows receiving PT. Bias ranged from 15 kg (scenario 1, PT level = 227 kg) to 893 kg (scenario 10, PT level = 2270 kg). The smallest t-statistic, based on 3 df and computed as mean bias divided by standard error of mean, was 17.6 ($P <$ .0002).

The last columns of Tables 5 and 6 express bias in PTA as a proportion of the PT level. According to these ratios, for example, if a cow receives a PT effect of 1000 kg according to scenario 1, then her PTA is biased by .06 x 1000 kg = 60 kg. As indicated by the ratios of bias to PT level, bias increased linearly as level of PT increased, within each scenario. Hence, the ratios in Tables 5 and 6 completely describe the results for a given

TABLE 5. Biases in PTA for scenarios 1 through 8.

Scenario	PT[1] Level	Bias $\bar{X}$	Bias SE[2]	Bias as ratio of PT level[3]
		----(kg)----		
1	227	15	.3	.06
	907	58	.8	.06
	2270	145	2.1	.06
2	227	22	.3	.09
	907	87	1.3	.09
	2270	217	3.2	.09
3	227	20	.4	.09
	907	79	1.5	.09
	2270	199	3.7	.09
4	227	29	.5	.13
	907	118	1.9	.13
	2270	295	4.9	.13
5	227	34	.9	.15
	907	135	3.7	.15
	2270	337	9.5	.15
6	227	33	.5	.15
	907	134	2.0	.15
	2270	334	5.0	.15
7	227	42	.4	.18
	907	166	1.5	.18
	2270	414	3.5	.18
8	227	45	.9	.20
	907	181	3.6	.20
	2270	452	9.0	.20

[1] Preferential treatment.
[2] Estimated standard error for mean bias.
[3] Computed as mean bias divided by PT level.

scenario. Furthermore, given that true PT effects are unknown, the ratios of bias to PT level are more informative than the mean biases. Means and standard errors were included so that formal comparisons among scenarios could be made and confidence intervals could be computed if desired.

Although ratio of bias to PT level was constant within each scenario, magnitude of bias varied across scenarios. As expected, biases were smallest in scenarios 1 and 2 (Table 5), where cows had a first record with no PT effect. In scenario 2, where cows had two records with PT, bias was 3% larger than in scenario 1, where cows had only one record with PT.

In scenarios 3, 4, and 5, where all records on selected cows received PT, bias increased as the number of PT records increased, but at a decreasing rate (Table 5). Cows with two records (scenario 4) had a 4% greater bias than cows with only one record (scenario 3); but addition of a third record with PT (scenario 5) increased bias by only an additional 2%. Biases in scenarios 3, 4, and 5 were increased by 5 to 6% when the dams of those cows also received PT (scenarios 6, 7, and 8).

Biases were largest in the flush scenarios (Table 6). Bias was computed separately for flush dams and flush daughters. Bias was larger for dams than for daughters in these scenarios because of the relationship structure among the cows that received PT. Different sires were used to generate daughters from the same dam. Thus, while dams had a .5 relationship to all of their daughters, a given daughter had a .5 relationship to only four other cows from her dam and only a .25 relationship to all other daughters from her dam. Increasing the number of flush daughters per dam from 10 (scenario 9) to 20 (scenario 10) increased bias on dams by 15% but increased bias on flush daughters by only 7%. In the flush scenarios, only 1 flush dam was allowed per herd but a given flush dam and all of her daughters were in the same herd. Therefore, some management groups had more than one PT cow. If

TABLE 6. Biases in PTA for scenarios 9 and 10.

	PT[1]	Bias		Bias as ratio
Item	Level	$\bar{X}$	SE[2]	of PT level[3]
	(kg)			
Scenario 9				
Dams				
	227	55	2.8	.24
	907	218	11.0	.24
	2270	546	27.6	.24
Daughters				
	227	36	1.7	.16
	907	143	6.7	.16
	2270	357	16.7	.16
Scenario 10				
Dams				
	227	89	4.6	.39
	907	357	18.4	.39
	2270	893	46.0	.39
Daughters				
	227	53	3.0	.23
	907	211	12.0	.23
	2270	530	29.9	.23

[1] Preferential treatment.
[2] Estimated standard error for mean bias.
[3] Computed as mean bias divided by PT level.

flush daughters had been put into different herds, and thus different management groups, bias on daughters probably would have been higher. If more than 1 PT cow is in a management group, it is reasonable to expect PT effects to resemble management effects more, relative to additive genetic effects, than if all PT cows were in different management groups.

In scenarios 1 through 8, mean bias divided by mean PT effect equaled the ratios reported in Tables 5 and 6 when PT effects were modeled as random variables rather than constants. In the flush scenarios, however, ratio of bias to PT effect decreased slightly for dams when PT effects were modeled as random variables. Mean bias, as a proportion of mean PT effect, was .22 and .32 for dams in scenarios 9 and 10, respectively. As expected, PT effects applied to flush daughters more nearly resembled an additive genetic effect of the dam when all daughters had the same PT effect.

Although the objective of this research was to examine bias in female PTA caused by PT, partitioning of the PT effect across all effects in the model allows more insight into how model effects are biased as PT is applied to different relatives and different records on the same animal. Because the proportion of PT effect partitioned into the animal term was constant within scenario, this complete partitioning was examined only for the second level of PT.

Partitioning of the PT effect across all terms in the model is given in Table 7 for each scenario. Management and sire by herd interaction effects accounted for the smallest portion of the PT effect in each scenario, while permanent environment, animal, and error tended to account for the largest portions. In general, as number of PT records on a given animal increased, or as relatives with PT were introduced, more of the PT effect was partitioned into permanent environmental and additive genetic effects and less into error.

In scenarios 1 and 2, where cows had first record with no PT effect, between 45 and 65% of the PT effect was partitioned into error, while most of the remaining portion was split about equally between permanent environment and animal effects. In scenarios 3, 4, and 5, between 35 and 60% of the PT effect was partitioned as additive genetic and permanent environmental effects and about 25 to 50% as error; permanent environment and animal effects again accounted for nearly equal portions. Also in scenarios 3, 4, and, 5, as total number of records for cows receiving PT increased, less of the PT effect was partitioned into error and more into permanent environment and animal effects. In scenarios 6, 7, and 8, where dams of cows from scenarios 3, 4, and 5 also received PT, the animal effect begins to account for more than the permanent environmental effect.

In the flush scenarios, the tendency continued for more of the PT effect to be partitioned into the animal effect and less into error and permanent environmental effects. Management effects accounted for noticeable portions of the PT effect for daughters in the flush scenarios which supports the previous argument that, bias in PTA would likely have been larger if related flush daughters had been placed in different herds. Although still a relatively small amount, sire by herd interaction accounted for 15% of the PT effect on daughters' records in scenario 10. Unlike sires in scenarios 1 through 8, sires of PT daughters in the flush scenarios had multiple PT

TABLE 7. Partitioning of preferential treatment (PT) effect across all model terms.[1,2]

Scenario	Management Effect[3] 1	2	3	4	PE	S x H	A	Error[3] 1	2	3	4
1	-.06	.09	NA	NA	.13	.05	.13	.75	.60	NA	NA
2	-.09	.07	.07	NA	.20	.06	.19	.64	.48	.48	NA
3	.13	NA	NA	NA	.17	.06	.17	.47	NA	NA	NA
4	.07	.05	NA	NA	.24	.09	.26	.34	.36	NA	NA
5	.06	.04	.04	NA	.29	.08	.30	.27	.29	.29	NA
6	.10	NA	NA	NA	.14	.05	.29	.42	NA	NA	NA
7	.06	.05	NA	NA	.21	.08	.36	.29	.30	NA	NA
8	.05	.04	.04	NA	.25	.07	.40	.23	.24	.24	NA
Scenario 9											
Dams	.05	.04	.04	NA	.16	0	.48	.31	.32	.32	NA
Daughters	.27	NA	NA	NA	.07	0	.31	.35	NA	NA	NA
Scenario 10											
Dams	.05	.04	.04	.07	.06	.04	.78	.07	.08	.08	.05
Daughters	.17	.09	NA	NA	.08	.15	.46	.14	.22	NA	NA

[1] NA = Not applicable for the indicated scenario;
Results computed as: average difference between biased and unbiased solutions, divided by PT level (907 kg), where biased solutions were those based on records with PT and unbiased solutions were those based on records without PT.
[2] PE = Permanent environmental effect; S x H = Sire by herd interaction effect; A = Animal effect;
[3] 1, 2, 3, 4 indicate lactation number.

daughters in each of several herds; therefore, sire by herd interaction was expected to account for more of the PT effect in the flush scenarios than in the other 8 scenarios. Sire by herd interaction did not account for much of the PT effect for dams in scenario 10 because flush dams were from different sires than flush daughters and so sires of flush dams had only a few offspring with PT and, furthermore, their PT offspring were not clustered in a small number of herds (maximum of one PT offspring per herd for sires of flush dams).

In contrast to scenario 10, sire by herd interaction did not account for any of the PT effect on daughters' records in scenario 9. However, management effect accounted for more in scenario 9 than in scenario 10. Thus, in the flush scenarios, daughters needed multiple records (as in scenario 10) before any of their PT effect was recognized as a sire by herd interaction. The tendency for sire by herd interaction to account for more of the PT effect, as number of PT records per cow increased, also occurred in the other scenarios but was just more pronounced in the flush scenarios. Sire usage was not a factor in the different partitionings for scenarios 9 and 10. Total number of sires of PT daughters was 4 in scenario 9 and 6 in scenario 10. Two and 4 bulls per herd were used as sires of PT daughters in scenarios 9 and 10, respectively. Thus, the total number of sire by herd interactions, involving at least 5 PT daughters, was 46 (2 x 23) for scenario 9 and 48 (4 x 12) for scenario 10. If permanent environment, sire by herd interaction, and animal are considered as permanent cow effects (factors affecting each record of the cow) and if management and error are considered as temporary environmental effects, then, as expected, more of the PT effect is partitioned into permanent cow effects as the number of records increases.

CONCLUSIONS

Results of this study clearly indicate the potential for bias, caused by PT in female PTA computed from the USDA animal model. Bias increased linearly as level of PT increased, for PT effects in the range of 227 kg to 2270 kg. Beyond the magnitude of the PT effect itself, several factors affect the extent of bias, including 1) whether PT has been practiced in second and later lactations only, or in all lactations, 2) total number of records for the cow receiving PT, and 3) the amount of relative information that has been inflated by PT. As more related animals received PT, the animal effect was increasingly biased. The PT on relatives increased bias more than increasing the number of PT lactations on a given animal. Biases were substantial; therefore, assuming that PT occurs in the U.S. dairy cattle population, methods to detect it and to correct for it in genetic evaluation are warranted.

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BIASES IN SIRE PREDICTED TRANSMITTING ABILITIES WHEN DAUGHTERS RECEIVE PREFERENTIAL TREATMENT[1]

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ABSTRACT

Data were simulated according to the USDA animal model primarily to determine biases in sire PTA when daughters receive preferential treatment. Two scenarios were investigated.

In scenario 1, all daughters were randomly distributed across herds. Bias increased with total number of daughters but at a decreasing rate. For a given total number of daughters, bias increased linearly as the percentage of daughters receiving preferential treatment increased from 25 to 100%. Expressed as a proportion of the preferential treatment effect, bias ranged from .10 to .77.

In scenario 2, daughters receiving preferential treatment were placed in a single herd and remaining, non-preferential treatment, daughters were randomly distributed across 378 other herds. Total number of daughters was 20, 30, or 40, and percentage receiving preferential treatment was 50, 75, or 100% in scenario 2. Two sets of herd sizes were used. With the smaller herds, bias was zero when all daughters received preferential treatment; otherwise, bias ranged from .08 to .10. With the larger herds, biases increased as the percentage of daughters receiving preferential treatment increased. The range in bias was .10 to .18 in scenario 2 for the larger herds.

INTRODUCTION

Popular opinion is that intentional preferential treatment (PT) occurs among US dairy cattle. Historically, a primary argument for the existence of PT has been that the cow index of bull-dams failed to predict PD of sons as accurately as theory dictated (5). Several studies (3, 4, 6) found that the cow index of bull-dams predicted son PD better when the cow index was based on first records only than when it was based on second and later records or when it was computed from all records. The typical conclusion from this result was that PT was practiced in second and later parities and was prompted by an outstanding first record.

In July 1989, however, USDA switched from the modified contemporary comparison system to an animal model for genetic evaluation of US dairy cattle. The question arose as to whether their (7) animal model evaluations were robust to PT. Using simulated data, Kuhn et al. (1) found that female predicted transmitting ability (PTA) can be substantially biased by PT. The magnitude of bias varied according to scenarios that were defined by combinations of three factors: 1) whether only second and later records or all records received PT 2) total number of records for the cow receiving PT and 3) whether only a single cow or a cow and her relatives (dam or dam and sibs)

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received PT. Within a scenario, bias increased linearly as PT increased.

The primary objective of this study was to determine biases in sire PTA when their daughters receive PT. A secondary objective was to determine the maximum number of daughters that can receive PT without seriously biasing PTA of their sire. A final objective was to determine the number of daughters a sire needs to get an approximately unbiased PTA when his dam has received PT.

MATERIALS AND METHODS

Kuhn et al. (1) found that the management effect of the USDA animal model accounted for more of the PT effect when multiple PT animals were placed in a single herd. Thus, bias in sire PTA was investigated for each of two scenarios. In the first scenario, all daughters were randomly distributed across herds; in the second scenario, all PT daughters were placed in a single herd, and remaining daughters were randomly distributed across other herds. There was a total of 379 simulated herds. Bias was estimated for each combination of two factors: total number of daughters for the bull whose daughters received PT (**NDAU**) and percentage of daughters receiving PT (**%PT**).

In scenario 1, NDAU ranged from 20 to 100 in increments of 10 and %PT was 25, 50, 75, or 100%. In scenario 2, NDAU was 20, 30, or 40, and %PT was 50, 75, or 100%. Two sets of herd sizes were used in scenario 2. In the first set, herd sizes were 62, 85, and 120 when NDAU was 20, 30, and 40, respectively. Furthermore, %PT also corresponded to the percentage of first lactation cows accounted for by the PT daughters with this first set of herd sizes. So, for example, when %PT was 50%, 50% of the sire's daughters received PT, and they accounted for 50% of the first lactation cows in their herd. The second set of herd sizes were 240, 343, and 446 for NDAU = 20, 30, and 40, respectively. For these herd sizes, daughters of a PT sire accounted for about 25% of the first lactation cows in their herd when %PT was 100%.

Because things such as magnitude of PT effects, number of daughters that actually received PT, or how many records of a bull-dam were inflated by PT would be unknown in practice, a few assumptions had to be made to address the secondary objectives of this study. Furthermore, definition of "seriously biased" or "approximately unbiased" was necessarily somewhat subjective. Hoyt (1994, personal communication) stated that 68 kg of PTA could make the difference between culling or keeping a borderline bull with his first proof. If the upper limit on PT effects is somewhere between 1361 and 2268 kg, then biases of 3 to 5% of the PT effect would be negligible or at least tolerable. Thus, the maximum number of daughters that can receive PT without seriously biasing the proof of their sire was taken to be the number that resulted in a bias of 3 to 5% of the PT effect. Similarly, to determine the number of daughters needed to override bias in son proof caused by PT of his dam, any bias between 3 and 5% of the PT effect was considered to be acceptable in this study.

General Approach

To evaluate the objectives of this study, the use of simulated data held some definite advantages over use of actual data; the true properties of simulated data are known and can be easily manipulated. With real data it is not possible to know the magnitude of PT effects; thus, statements about magnitude of bias in PTA, caused by PT, would not be possible with real data as it is with simulated data. Hence, the general approach to addressing the primary objective was as follows: 1) data with no PT effects were simulated according to the USDA animal model (7); 2) unbiased PTA based on non-PT records were computed; 3) a single bull with the desired NDAU was selected; 4) PT effects were added to the appropriate number of daughters; 5) biased PTA based on PT records were computed; and 6) bias was computed as biased PTA minus unbiased PTA.

The same general approach was used for the secondary objectives except to determine the number of daughters needed to get an approximately unbiased proof when the sire's dam received PT. PT was, of course, added to dam records rather than to daughter records.

Simulation of Data

The simulation program that was written and utilized by Kuhn et al. (1) also was used in this study. Simulated populations in this study had the same properties as their (1) populations of 30.000 cows and are described in detail by Kuhn et al. (1). Therefore, only a brief description of the simulation is given.

The model for simulation of records was the USDA animal model used to compute national genetic evaluations for dairy cattle (7, 8). The model equation can be written as

$$y = M + PE + (S \times H) + A + e \quad [1]$$

where y is phenotypic milk record M is management group effect PE is permanent environmental effect S x H is sire by herd interaction effect A is animal effect and e is a residual effect. Definition of management groups is that used by the USDA for computation of the national evaluations (8).

Management group effects (M) were generated as

$$M = H + Y + S + P + R + HYSPR \quad [2]$$

where H, Y, S, P, and R are herd, year of calving, season of calving, parity, and registration effects, respectively, and HYSPR is herd-year-season-parity-registration interaction effect, which is unique to a particular management group.

Aspects of population structure, such as herd sizes and frequency of herd sizes, relative frequencies of registered and grade cows, season of calving frequencies, parity frequencies, generation intervals, and relationship structure, were all comparable with those for the US Holstein population and are given by Kuhn et al. (1).

Selection of Sire and PT Effects

The total number of years for simulation was 20. Twenty-one new progeny test bulls were created each year up to yr 16. Progeny-test bulls were not created beyond yr 16 because they would not have had daughters with records by yr 20.

For choosing a bull whose daughters were to receive PT, a single sire was randomly chosen from among the final set of progeny-test bulls that had the desired NDAU. Daughters from the final set of progeny-test bulls did not make their first record until the final year of simulation, so each daughter of a selected sire had only a single record. The PT effects were added to the phenotypic records simply by adding either 453, 906, or 1359 kg to the non-PT record. These levels were added in relative frequencies such that average PT effect was 906 kg.

PT and Estimation of Bias

Table 1 outlines the design used to estimate bias for one level of the NDAU factor. For any particular NDAU by %PT combination, represented by, say, row 1 of Table 1, the procedure was to obtain four statistically independent estimates of bias (X_{i11}, X_{i12}, X_{i13}, X_{i14}) and then compute the simple average of the four replicate values ($\bar{X}_{i1.}$). An estimate of the standard error of $\bar{X}_{i1.}$ was computed as the square root of the variance among the replicate values. The overall statistics (labeled as $\bar{X}_{ij.}$ and SE in Table 1) then were used as the statistics for inference. For each replicate, bias (X_{ijk}) was computed as biased PTA minus unbiased PTA for the bull whose daughters received PT. The same procedure was used to estimate bias for each combination of NDAU and %PT.

TABLE 1. Outline of design used for estimation of bias.

		Replicate[3]				Overall[4]	
NDAU[1]	%PT[2]	1	2	3	4	$\bar{X}_{ij.}$	SE
i	25	X_{i11}	X_{i12}	X_{i13}	X_{i14}	$\bar{X}_{i1.}$	s_{i1}
	50	X_{i21}	X_{i22}	X_{i23}	X_{i24}	$\bar{X}_{i2.}$	s_{i2}
	75	X_{i31}	X_{i32}	X_{i33}	X_{i34}	$\bar{X}_{i3.}$	s_{i3}
	100	X_{i41}	X_{i42}	X_{i43}	X_{i44}	$\bar{X}_{i4.}$	s_{i4}

[1]Total number of daughters.
[2]Percentage of daughters receiving preferential treatment.
[3] X_{ijk} = bias in sire PTA at NDAU level i (i = 1, 2, ..., 9) and %PT j (j = 1, 2, 3, 4) and in replicate k.

[4] $\bar{X}_{ij.}$ = Simple average of the four replicate means; s_{ij} = standard error of $\bar{X}_{ij.}$

The ratio of overall mean bias ($\bar{X}_{ij.}$ in Table 1) divided by level of PT also was calculated for each NDAU by %PT combination. The ratios of bias to PT level are a more informative way to describe bias because true PT effects would not be known in practice; actual biases, expressed in kilograms of PTA, depend on the level of PT received by the daughters, but the ratios hold, regardless of PT level.

Computation of PTA

The PTA were computed as one-half times actual animal solutions from the USDA animal model (Equation [1]). Management effects were assigned to records in the simulation of data according to Equation [2], regardless of group size. If, however, group size was <5, groups were combined according to the algorithm utilized by the USDA (8). Animal model solutions were obtained using the JAA program of Misztal (2).

Data included all records on all non-base cows. Records on base cows were not included in the calculation of solutions because their sires were unknown (8). The relationship matrix was complete back to base animals. Each replicate, had 210,829 cow, 367 sire, and 174,245 permanent environmental (equal to number of nonbase cows) solutions.

RESULTS AND DISCUSSION

Bias in sire PTA when PT daughters are randomly distributed across herds

Biases for each NDAU by %PT combination, when all daughters were randomly distributed across herds, are presented in Table 2. The biases are expressed as ratios to the average PT effect on daughters. According to these ratios, for example, if mean PT effect for daughters is 1000 kg and the bull has 20 daughters, 25% with PT, then the bias in his PTA is .10 x 1000 kg = 100 kg. All mean biases were significantly different from zero. The smallest *t* statistic, based on 3 df and computed as mean bias divided by standard error of mean, was 10.1 ($P <$ .0011).

TABLE 2. Biases in sire PTA when daughters were randomly distributed across herds.[1]

	Total number of daughters								
%PT[2]	20	30	40	50	60	70	80	90	100
25	.10	.12	.14	.15	.17	.17	.18	.19	.19
50	.21	.26	.29	.32	.34	.35	.37	.38	.39
75	.32	.38	.44	.48	.51	.52	.57	.57	.60
100	.42	.52	.59	.65	.68	.71	.73	.75	.77

[1]Biases are expressed relative to the mean effect of preferential treatment.
[2]Percentage of daughters receiving preferential treatment.

Bias increased as NDAU increased but at a decreasing rate. As a function of NDAU, increase in bias was small to nil when NDAU was ≥60. By far, the major factor affecting bias was %PT. Increase in bias was essentially linear for a given NDAU as %PT increased from 25 to 100%. The amount of linear increase varied, however, according to NDAU when NDAU was ≤60. Thus, there was interaction between NDAU and %PT; the effect of NDAU became less as NDAU increased. The effect of NDAU on bias decreased as NDAU increased because the importance of daughter information relative to ancestor and collateral information was increasing up to about 60 daughters.

Biases in sire PTA when PT daughters were placed in single herd

Smaller Herd Sizes. Biases are presented in Table 3 for scenario 2 for the case in which PT daughters were placed in the smaller herd sizes. Bias decreased considerably relative to the case in which daughters were randomly distributed across herds. When NDAU was 20 and %PT was 50%, for example, bias was .21 when daughters were randomly distributed across herds and only .08 when all PT daughters were in the same herd. Increased proportion of PT daughters in one herd from .5 to .75 had little effect on bias, but placement of all PT daughters in a single herd reduced bias to zero because PT daughters accounted for all first lactation cows when %PT was 100% and, thus, they were all contemporaries. Although tangential to the objectives of this study, this result confirms that use of bST would not be expected to bias genetic evaluations provided that it is used the same way on all cows in a management group and that no interaction exists between response to bST and true breeding value.

TABLE 3. Biases in sire PTA when daughters receiving preferential treatment (PT) are placed in a single smaller herd.[1]

	Total number of daughters		
%PT[2]	20	30	40
50	.08	.09	.09
75	.07	.09	.10
100	0	0	0

[1]Biases are expressed relative to the mean PT effect.
[2]Percentage of daughters receiving PT.

The management effect of daughters accounted for more of the PT effect as %PT increased when PT daughters were placed in a single herd. However, sire by herd interaction for daughters accounted for less of the PT effect as %PT increased from 50 to 75%. Thus, magnitude of bias in sire PTA either changed little or actually increased slightly when %PT increased from 50 to 75% (Table 3).

Larger Herd Sizes. Biases are presented in Table 4 for scenario 2 for the case in which PT daughters were in a single, larger herd. In general, biases were larger when PT daughters were placed in a single, larger herd because PT daughters accounted for, at most, about 25% of the first lactation cows in their herd and, therefore, had contemporaries that did not receive PT. The amount of the PT effect accounted for by the management effect of PT daughters changed very little as %PT (and thus number of PT daughters in one herd) increased because of the relatively large herd size. Therefore, unlike the case for the smaller herds, biases increased as %PT increased. NDAU had almost no effect on biases when PT daughters were placed in the larger herds.

Although effectiveness of sire by herd interaction in accounting for PT did decrease as %PT increased, the decrease was small. Furthermore, even when %PT was 100%, sire by herd interaction of PT daughters still accounted for nearly 50% of the PT effect.

TABLE 4. Biases in sire PTA when daughters receiving preferential treatment (PT) are placed in a single larger herd.[1]

	Total number of daughters		
%PT[3]	20	30	40
50	.10	.10	.10
75	.13	.14	.14
100	.16	.18	.18

[1]Biases are expressed relative to the mean PT effect.
[2]Percentage of daughters receiving PT.

Secondary Objectives

In general, only about 5 to 6% of a bull's daughters could receive PT without inflating the proof of their sire by more than 5% of the PT effect (Table 5), when all daughters are randomly distributed across herds.

Kuhn et al. (1) found that bias in female PTA increased as total number of records on the cow increased. As indicated in Table 6, only 30 daughters would be needed to get an approximately unbiased proof on the sire. even when the dam has as many as three records, each with PT. Only dam records received PT in this part of the study. If, in addition, other relatives (e.g., sibs, maternal granddam, daughters) receive PT, then more daughters without PT would be needed to get an approximately unbiased proof.

TABLE 5. Maximum number of daughters that can receive preferential treatment (PT) without biasing the proof of their sire by more than 5% of the PT effect.

NDAU[1]	NPT[2]	Bias[3]
20	1	.021
30	2	.044
40	3	.044
50	3	.036
60	4	.044
70	4	.040
80	4	.035
90	5	.043
100	5	.040

[1]Total number of daughters.
[2]Number of daughters receiving PT.
[3]Biases are expressed relative to the mean PT effect.

TABLE 6. Number of daughters needed when dam has received preferential treatment (PT).

Records on dam	Daughters	Bias[1]
----------(no.)----------		
1	20	.025
2	20	.038
3	30	.032

[1]Bias expressed relative to mean PT effect.

CONCLUSIONS

Results of this study clearly indicate the potential for bias in sire PTA computed from the USDA animal model, when daughters receive PT. For a given NDAU, bias increased linearly as %PT increased from 25 to 100% when all daughters were randomly distributed across herds. Bias depends on NDAU when NDAU ≤60. Magnitude of bias decreases when all daughters receiving PT are placed in a single herd, but the amount of decrease depends on the herd size of the PT daughters. Although dependent on the level of PT effect, probably no more than 5 to 6% of a bull's daughters can receive PT without placing the bull's proof into serious question, at least when PT daughters are randomly distributed across herds. If only a sire's dam has received PT, then 20 to 30 daughters without PT are sufficient to obtain an approximately unbiased proof on the bull, provided that the PT effect on the dam was not too high (say, PT effect ≤2268 kg). Bias in sire PTA, when daughters receive PT, can be substantial; therefore, assuming that PT occurs in the US dairy cattle population, methods to correct for it in genetic evaluation are warranted.

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APPROACHES INVESTIGATED TO CORRECT FOR PREFERENTIAL TREATMENT

A paper prepared for submission to the Journal of Dairy Science

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ABSTRACT

Simulated data were used to investigate the effectiveness of three approaches to correcting for preferential treatment in genetic evaluation of U.S. dairy cattle. Methods tested included power transformations applied to the phenotypic records, fitting a random preferential treatment effect to suspect records defined according to magnitude of residual, and a two-group mixture model. Transforming records with a power of .1 reduced bias to zero but had a very adverse effect on ranking. Fitting a random preferential treatment effect in the model for genetic evaluation was effective in reducing bias, given an appropriate variance for the preferential treatment effect, but preferential treatment records were typically identified only 45 to 60 percent of the time. Reductions in bias brought about by the mixture model were small but were accomplished without any negative effects on ranking. Although not yet ready for use in practice, results for both the random preferential treatment effect and mixture model approaches were favorable enough to warrant further development of these methods as possible approaches to correcting for preferential treatment in genetic evaluation.

INTRODUCTION

Preferential treatment (PT) can be described as any management practice that increases production and is applied to one or several cows but is not applied to their contemporaries. Some of these practices might be separate housing, better or more feed, greater number of days open relative to contemporaries, longer milking intervals on test day, or non-uniform use of BST within a herd. Some PT may occur inadvertently through the use of routine management practices but which are not applied to all cows equally. A commonly recommended practice, for example, is to feed cows according to their level of production. Non-uniform use of BST may just be part of the management for a given herd rather than an attempt to intentionally bias an animal's predicted transmitting ability (PTA).

Kuhn et al. (3) found that PT, applied to elite cows, causes substantial biases in their PTA. Biases ranged from six to 39 percent of the PT effect, depending on number of records for the PT cow, whether all or only second and later records received PT, and whether or not relatives of the PT cow also received PT. While primary interest may be in the effect of PT on the PTA of elite cows, there is also concern about its effect on sire PTA when their daughters receive PT. Kuhn and Freeman (2) found biases in sire PTA ranging from 10 to 77 percent of the PT effect, depending on total number of daughters for the sire and proportion of those daughters receiving PT. For a bull having 40 daughters, only 10 of these daughters receiving PT, bias in his

PTA would be 14% of the average PT effect on his daughters. If the average PT effect on his daughters was 1350 kg, the bias in his PTA would be about 190 kg.

With the advent of BST, more widespread use of technologies which allow individualized cow care (e.g., computerized grain feeders), and a tendency by artificial insemination (AI) organizations to use bulls with only first progeny test as sires of new sires, PT is perhaps of even more concern now than in the past. Given these concerns and the fact that PT can seriously bias both male and female PTA, methods to correct for it are warranted. The objective of this research was to investigate the effectiveness of several methods in correcting for bias in PTA caused by PT.

Three approaches to correcting for PT were tested: 1) power transformations applied to all phenotypic records 2) a random PT effect included in the model for genetic evaluation, henceforth called the "random PT" (**RPT**) method and 3) a mixture model.

Which cows or records receive PT will not, of course, be known with certainty in the real population. Thus, methods applied to correct for PT will likely have some effect on non-PT records as well. An optimum correction would not only reduce bias in PTA caused by PT but also have little or no adverse effect on ranking, relative to the case of using no correction. Therefore, two aspects of each method were examined: 1) effectiveness in reducing bias caused by PT and 2) effect on ranking, relative to the case of no correction.

MATERIALS AND METHODS

Simulated data were used to test all methods examined. The general approach was to simulate data according to the USDA-AIPL animal model for genetic evaluation, and with a population structure comparable to that of the actual US Holstein population; apply PT to selected records; apply the method for correction; and compute bias and the effect of the method on ranking. The effect on ranking was examined by comparing mean true transmitting ability (**TA**) of the top 5 or 10% of cows, based on PTA with and without the correction. Characteristics of the simulated populations are described in detail in Kuhn et al. (3) and Kuhn and Freeman (2).

The USDA animal model can be written as:

$$\mathbf{y} = \mathbf{Xm} + \mathbf{Z_1 pe} + \mathbf{Z_2 sh} + \mathbf{Z_3 a} + \mathbf{e} \qquad [1]$$

where y is a vector of observations, and **m** is a vector of fixed management effects defined according to herd, year, season, parity, and registry status. The vectors **pe**, **sh**, **a**, and **e** are the random effects of permanent environment, sire by herd interaction, animal, and error, respectively. $\mathbf{X}$, $\mathbf{Z_1}$, $\mathbf{Z_2}$, and $\mathbf{Z_3}$ are incidence matrices relating effects to observations in y. In the simulation, permanent environment, sire by herd interaction effects, and errors were all normally distributed with expectation zero and variance, $\mathbf{I}\sigma_i^2$. Animal effects were also normally distributed with expectation zero for base animals and $.5(BV_S + BV_D)$ for non-base animals where BV_S is breeding value of the sire and BV_D is breeding value of the dam. Var(**a**) was $\mathbf{A}\sigma_a^2$ where **A** is the additive relationship matrix. $Var(y) = \mathbf{Z_1 Z_1}'\sigma_{pe}^2 + \mathbf{Z_2 Z_2}'\sigma_{sh}^2 + \mathbf{Z_3 A Z_3}'\sigma_a^2 + \mathbf{I}\sigma_e^2$.

POWER TRANSFORMATIONS

The effect of PT is to move phenotypic records toward the upper end of the phenotypic distribution. The motivation for the power transformations was that, for powers less than one, the transformation will reduce larger records more than smaller records. As an example, consider a power transformation using a power of .5 and suppose two cows would each make a record of 8100 kg, if no PT was practiced, but one of the records was inflated to 9025 kg by PT. The transformed records would be 90 (square root of 8100) and 95 kg (square root of 9025). The difference between these records should be zero; on the original scale, the difference is 925 but on the transformed scale the difference is only 5.

Four powers were investigated for their effectiveness in reducing bias in PTA caused by PT: .1, .3, .5, and .7. The procedure was to simply take each phenotypic record to the indicated power. One appealing aspect of this approach, therefore, was computational ease. Another favorable aspect, relative to methods which either implicitly or explicitly identify certain records as having received PT, is that all records would be treated the same which would prevent potential conflicts with producers.

One problem in studying the effectiveness of the power transformations was that the PTA were on different scales for the different powers. Thus, a bias of "100," for example, would not mean the same thing for .7 transformation as for a .3 transformation. For the sake of comparing biases across the different powers, bias was computed in standard deviation units by first expressing PTA in standard deviation units.

RPT METHOD

This approach first attempts to identify possible PT records and then a random PT effect is included in the model for genetic evaluation.

Identification of records as "suspect" was based on magnitude of residuals computed as $\hat{e} = y - X\hat{m}$, where $\hat{m}$ is the solution for m in model [1]. In preliminary results, this "management group residual" resulted in better identification than did the "full model residual": $y - X^*\hat{m} - Z^*\hat{u}$, $\mathbf{Z} = (\mathbf{Z}_1, \mathbf{Z}_2, \mathbf{Z}_3)$ and $\mathbf{u} = (\mathbf{pe}, \mathbf{sh}, \mathbf{a})$. This was likely due to solutions for **pe** and **a** containing a significant portion of the PT effect and thus removing it from the residual.

The management group residuals were standardized according to their individual standard deviations. $\mathrm{Var}(\hat{e})$ was computed as $\mathrm{Var}(y) - \mathbf{XC}_{11}\mathbf{X}'\sigma_e^2$ where C_{11} is that portion of the inverse of the coefficient matrix of the mixed model equations (1), corresponding to the fixed effects. Derivation of this expression is given in the appendix.

Once the standardized management group residuals were computed, a decision had to be made as to what constituted a "large" residual. The first approach was to just set an essentially arbitrary value, such as 3.0, and define any residual with that value or larger as a suspect PT record. This, however, resulted in considerable variation among replicates in the proportion of records identified as suspect. In extreme cases, for example, there were no residuals ≥ 3.0. Although PT records did tend to have larger residuals, relative to other records, what constituted "large" varied from one replicate to the next. The procedure used, therefore, was to define the largest p percentage of residuals as suspect for PT. Different levels of p (1, 2, 3, 4, and 5 percent) were investigated to determine which resulted in the most optimum correction.

After identification of suspect records, the following model was fit:

$$\mathbf{y} = \mathbf{Xm} + \mathbf{Z_1pe} + \mathbf{Z_2sh} + \mathbf{Z_3a} + \mathbf{Z_4pt} + \mathbf{e} \qquad [2]$$

which is model [1] except with the additional term, $\mathbf{Z_4pt}$. $\mathbf{Z_4}$ is an n x t matrix of 1's and 0's, n = number of records in y and t = number of suspect records + 1. pt was a t x 1 vector of unknown, random "PT effects." Each of the t suspect records had its own, separate PT level and all other records were in the same PT group. A small sample $\mathbf{Z_4}$ matrix is given in Table 1.

Table 1. Example Z_4 matrix for the RPT correction[1].

1	0	0	0
0	1	0	0
0	0	1	0
0	0	0	1
0	0	0	1
0	0	0	1
0	0	0	1
0	0	0	1

[1]In this example, three records were identified as suspect, thus four levels for the pt factor. The first three rows would correspond to the suspect records and the last five rows to all other records.

PT was fit as a random, rather than fixed, effect for several reasons. In practice, PT effects will vary from one cow to the next and probably even from one record to the next for the same cow. The random PT effect allows for these different levels without making the residual zero for suspect records. Furthermore, in a preliminary analysis, PT was fit as a fixed effect with two levels, one for non-PT records and one for suspect records. This grossly over-adjusted the PT records, resulting in a large negative bias in PTA for those cows in the PT group.

The variance for the pt factor (σ^2_{pt}), used to solve the mixed model equations for model [2], was obtained empirically. Model [2] was fit allowing for σ^2_{pt} to account for 3.3, 4.2, or 8.5 percent of the total variance. This was done in a preliminary analysis and the variance giving the most desirable results was then used in all subsequent replicates.

Because inversion of the coefficient matrix was required, simulated population size was considerably smaller than that of (3). There were 223 milking cows per year, simulated over a 10 year span giving a total of 830 cows and 1405 records. Only two cows, with a single record each, were given PT. Two levels of PT were used, 905 kg and 1358 kg. Ten replicates were done for each combination of PT level and percentage of records defined as suspect. Cows were selected for PT based on magnitude of parent average PTA. Also because of small sample size, elite cows were defined as top 10% for investigating effect of the RPT correction on ranking.

MIXTURE MODEL

Description of mixture model and aspects tested. The (finite) mixture model examined in this study considered two groups of records: those receiving and not receiving PT. The model equation can be written as:

$$\mathbf{y} = \mathbf{X_1 m} + \mathbf{X_2 pt} + \mathbf{Z_1 pe} + \mathbf{Z_2 sxh} + \mathbf{Z_3 a} + \mathbf{e} \quad [3]$$

which is model [1] with the additional term, $\mathbf{X_2 pt}$. $\mathbf{pt}$ is a 2x1 vector of means, corresponding to the two groups of records (with and without PT) and $\mathbf{X_2}$ is an unknown, nx2 matrix of probabilities, n = number of records. For the ith row of $\mathbf{X_2}$, column one is the probability that the ith record received PT and column two is the probability that the ith record did not receive PT.

There are two aspects to utilizing model [3] as a means to correct for PT. One aspect is obtaining estimates of the mixture parameters which includes means of the PT and non-PT groups, and relative frequency (or unconditional probability) of PT in the population. These parameters are needed to calculate the $\mathbf{X_2}$ probabilities. The other aspect of model [3], then, is calculation of the $\mathbf{X_2}$ probabilities, given the mixture parameters, and subsequent adjustment of the data given the matrix $\mathbf{X_2}$. This research tested the latter aspect, correcting for PT using model [3], given values for the mixture parameters. If the mixture model is not effective in correcting for PT, given the true values for the mixture parameters, then research aimed at estimation of the PT parameters would not be warranted.

Model [3] was tested under several sets of mixture parameters. Values for the relative frequency of PT in the population were .01, .05, and .1. Mean for the PT group or, equivalently, the PT effect, was 905, 1358, and 2263 kg. Mean for the non-PT group was always zero.

The viewpoint of only two PT groups is a simplification since, in practice, PT effects will vary from one PT record to the next. The number of groups, however, can be considered as another mixture parameter to be estimated. Furthermore, if the mixture model proved effective in correcting for PT, the 2-group model could be tested for adequacy under conditions where there was actually more than one level of PT.

Adjustment for PT. Since the means of the two PT groups were considered known in this study, the correct approach to adjusting for the PT effect would be to either place a restriction on the mixed model equations, specifying the PT means, or, equivalently, do a prior additive adjustment: $\mathbf{y_{adj}} = \mathbf{y} - \mathbf{X_2 pt}$, where $\mathbf{pt}$ is the 2x1 vector of group means. Because it is simpler, the additive adjustment was used to correct the data for PT and the corrected data was used to compute PTA according to model [1].

Fitting model [3]. An iterative procedure was used to fit model [3]. First, $\mathbf{y_{adj}} = \mathbf{y} - \mathbf{X_2 {*} pt}$ was computed, given X_2; model [1] was then fit to y_{adj}; probabilities in X_2 were then recomputed using residuals, $r_i = y - X_1 {*} \hat{m} - Z_1 {*} \hat{pe} - Z_2 {*} \hat{sh} - Z_3 {*} \hat{a}$, where $\hat{m}$, $\hat{pe}$, $\hat{sh}$, and $\hat{a}$ were solutions from step 2. Iteration was then carried out by returning to step 1 and continuing until convergence was achieved.

Calculation of X_2 probabilities. The conditional probabilities, probability of PT given r_i ($\Pr(PT|r_i)$) and probability of non-PT given r_i ($\Pr(\text{non-}PT|r_i)$), were calculated as:

$$\Pr(PT|r_i) = \frac{pf_1}{(pf_1 + (1-p)f_2)} \qquad \Pr(\text{non-}PT|r_i) = \frac{(1-p)f_2}{(pf_1 + (1-p)f_2)} \qquad \text{where,}$$

p = relative frequency (or unconditional probability) of PT in the population

$f_1 = c * \exp[-(r_i - \mu_{PT})^2/2\sigma_e^2]$ $f_2 = c * \exp[-(r_i - \mu_{NOPT})^2/2\sigma_e^2]$

μ_{PT} = mean of PT group μ_{NOPT} = mean of non-PT group

$c = 1/(2*pi*\sigma_e^2)^{.5}$

A small example of an X_2 matrix is given in Table 2.

Table 2. Sample X_2 matrix.

	X_2	
Record	$Pr(PT\|r_i)$ (column 1)	$Pr(non\_PT\|r_i)$ (column 2)
1	.00457	.99543
2	.02100	.97900
3	.84173	.15827
4	.54329	.45671
5	.32278	.67722
6	.00003	.99997
7	.98912	.01088

1. Records 3, 4 and 7 are PT records; the other four are non-PT records.

General approach for testing mixture model. The general procedure for testing the effectiveness of the mixture model was to 1) simulate data with PT effects; 2) compute X_2, given the data and the PT parameters; 3) adjust the data, given X_2; 4) compute PTA using the adjusted records; 5) compute bias as PTA - TA. There were 20 replicates for each of the nine combinations of mixture parameters.

One aspect of the mixture model, illustrated in Table 2, is that records not inflated by PT will also be regressed somewhat because $Pr(PT|r_i)$ will not, in general, be zero for these records. It is conceivable, then, that the mixture model could also lead to rankings that are less correct than if no adjustment was done. Thus, the potential cost of the mixture model was also examined by computing the mean true TA of the top five percent of all cows when ranking was based on both adjusted and unadjusted PTA.

Cows receiving PT. For a given relative frequency of PT, two sets of cows were preferentially treated. One set was randomly selected from among all cows and the other set was comprised of cows randomly selected from among the top 5%. Elite cows were specifically chosen for PT because they may be the most likely candidates for intentional PT, given their potential use as a dam of new sires for progeny testing. Criterion for the highest 5% was dam's deviation from contemporaries. All elite cows, selected for PT, had a single record.

Cows randomly selected for PT had two records and PT was applied to both records. A random selection of cows for PT was made for several reasons. First, cows might be selected for PT on traits other than production, such as type, which have fairly low correlations with production. Furthermore, random selection of cows may be a better model for inadvertent PT. Secondly, model [3] assumes cows receiving PT were selected at random. Thus, if model [3] did not satisfactorily correct for PT when applied to elite cows, but did when applied to randomly selected cows, better modeling of the PT might be warranted rather than complete rejection of the mixture model as a means to correct for PT. Finally, the percentages of records receiving PT (.01, .05, .10) were too high to be used on elite cows only.

RESULTS AND DISCUSSION

POWER TRANSFORMATIONS

Bias, in standard deviation units, is given in Table 3 for the case of no transformation and for each of the powers tested. Powers of .3, .5, and .7 had little to no effect on bias but transforming with a power of .1 reduced bias to zero. The problem, however, with the .1 transformation was that it had very negative effect on ranking. Mean true TA of the top 5% was about 905 kg less when ranking was based on transformed PTA than when ranking was based on non-transformed PTA. Clearly, the data did not fit the linear model after applying the non-linear transformation. Attempts to circumvent this problem, such as applying the inverse transformation to the PTA computed from the transformed records and trying various variance ratios in computing solutions, were not successful.

Table 3. Bias in PTA computed from transformed records.

Power	Bias in standard deviation units
1	.083
.7	.086
.5	.082
.3	.078
.1	0

RPT

Variance for fitting random PT effect. Table 4 gives mean bias and mean TA of the top 10% for the cases of no PT in the data or model, PT in the data but not in the model, and PT in the data and in the model for each of the three variances tested. Allowing PT to account for only 3.3% of the total variance resulted in bias closest to zero. There was no difference in mean TA of the top 10% for rankings based on the different sets of PTA. Thus, variance of the PT factor was set at 3.3% of the total variance in all replicates. In this preliminary analysis, both PT cows were included as suspects and bias in PTA was essentially zero.

Identification of PT records. Table 5 illustrates the success rate of identifying PT records based on magnitude of management group residual. As expected, identification of PT records improved as magnitude of PT effect increased and as proportion of records defined as suspect increased. For the 905 kg PT effect, identification was poor when percent defined as suspect was 2% or less. When percent defined as suspect was 3% or greater, identification of PT records improved to nearly 50%.

Table 4. Preliminary analysis to determine appropriate variance for PT factor.

Variance of[1] PT factor	Mean bias (kg)	Mean[2] TA (kg)
0	0	723
0	95	723
3.3	-3	681
4.2	-17	681
8.5	-61	681

[1]First row corresponds to no PT in the data or model; second row to PT in the data but not in the model; last 3 rows to PT in the data and the model where variance given is proportion of total variance.
[2]Mean true transmitting ability of top 10% of cows when ranking is based on the corresponding PTA.

Table 5. Identification rate of PT records[1].

	905 kg PT effect					1358 kg PT effect				
Rep	1%	2%	3%	4%	5%	1%	2%	3%	4%	5%[2]
1	2	2	2	2	2	2	2	2	2	2
2	0	1	2	2	2	2	2	2	2	2
3	0	0	0	0	0	0	0	0	0	0
4	1	1	1	1	1	1	1	1	1	1
5	0	1	2	2	2	2	2	2	2	2
6	0	0	0	0	0	0	0	1	1	2
7	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	1	1	1
9	1	1	1	1	1	1	1	1	1	1
10	0	1	1	1	1	1	1	1	1	1
Total[3]:	4	7	9	9	9	9	9	11	11	12

[1]Numbers in table are the number of PT records detected for each of the 10 replicates, two cows received PT.
[2]Percent of records defined as suspect.
[3]Maximum, and ideal, total for any column = 20 = 2 PT cows per rep x 10 reps.

For the 1358 kg PT effect, identification of PT records was nearly 50%, even when percent defined as suspect was 2% or less. When percent defined as suspect was 3% or higher, given the 1358 kg PT effect, identification of PT records was between 50 and 60 percent.

Mean bias for cows receiving PT. Mean biases in PTA, for cows receiving PT, are given in Table 6. These biases were essentially a function of the magnitude of the PT effect and the proportion of PT cows identified. With only 2% defined as suspect, the largest bias was only 66 kg of PTA. When percent defined as suspect was 3% or higher, the largest bias was only 43 kg of PTA. The RPT approach was effective in reducing mean bias in PTA, caused by PT.

Effect on ranking. The cost, in terms of mean true TA of top 10%, associated with the RPT correction (Table 7) was small. Mean true TA for the top 10% was at most 30 kg less when ranking was based on PTA using the RPT correction compared to ranking based on uPTA (PTA with no PT in the data or model). And this cost is probably overstated, relative to what it would be in practice, because the simulated conditions were quite

Table 6. Mean bias in PTA for cows receiving PT.

Percent defined as suspect[1]	Mean bias, kg PTA 905 kg PT effect	1358 kg PT effect
0	95	138
1	69	87
2	36	66
3	13	43
4	7	36
5	4	23

[1]First line corresponds to bias when there was no correction for PT.

stringent for this comparison. Only two cows per replicate received PT and these cows already belonged in the top 10% based on uPTA. A higher frequency of PT likely exists in the real population and with a higher frequency, this cost would be less or perhaps non-existent, depending on whether or not the cows actually belonged in the top 10%. Rank correlations of uPTA with all other PTA computed were quite high.

Table 7. Effect of the random PT correction on ranking.

PTA[1]	Rank Correlation[2]	Mean true TA (kg)[3]
uPTA	1.0	592
bPTA	.9989	592
PTAp1	.9974	583
PTAp2	.9942	579
PTAp3	.9901	572
PTAp4	.9846	562
PTAp5	.9800	566

[1]uPTA is PTA without PT in the data or model: bPTA is PTA with PT in the data but not in the model: PTAp1, PTAp2, PTAp3, PTAp4, and PTAp5 are PTA using the RPT with 1, 2, 3, 4, and 5% of the records defined as suspect, respectively.
[2]Correlation between ranks based on uPTA and the indicated PTA.
[3]Mean true TA of top 10% of cows when ranking is based on the indicated PTA.

General discussion. The PT effects used to test the RPT method were probably only small to moderate, relative to what they may be in practice. PT effects in the range of 1800 to 2300 kg are probably quite feasible. As PT effects increase in size, the effectiveness of the RPT correction improves because PT records are more frequently identified. The RPT correction could be expected to remove at least the most serious biases in female PTA, caused by PT. The cost associated with this method will also be lower with larger PT effects, particularly if PT is applied to cows other than elite cows.

Given the uncertain nature of PT, it may not be practical to require a correction method which removes nearly all bias due to PT and which has no potential cost associated with it. Some arbitrary but reasonable compromise, based on simulated results which illustrate both benefits and potential costs of a method, may have to be made between reducing bias in PTA caused by PT and the effect of the method on PTA from non-PT cows.

Further development of the RPT correction should first focus on finding either a rapid method or an approximation for computing Var($\hat{e}$). Inversion of the coefficient matrix is not feasible in practice and if an approximation is used, that should be part of the test for the utility of the RPT correction.

Beyond that, the most difficult aspect is the identification step. When PT records are identified, the random PT effect is effective in reducing bias in PTA caused by PT, given an appropriate variance for the PT effect. There are several aspects to the identification step which warrant further address. First, it is not entirely clear how to best define "large" residuals. It may be adequate, however, to simply define an arbitrary proportion as suspect, as was done in this study, giving consideration to the fact that as the proportion increases more PT records are detected but the cost also increases and that the largest PT effects will probably be detected even with a small proportion defined as suspect. The other aspect of identification is accuracy. Any increase in the frequency of identifying PT records and decrease in the number of false positives would reduce both mean bias due to PT and potential cost associated with the RPT correction. One possibility to improving the accuracy of identification might be to use the full model residual in a short, iterative procedure. The procedure would be to 1) fit model [1] to the original records; 2) compute the management group residuals, $\mathbf{y} - \mathbf{X}\hat{\mathbf{m}}$; 3) define top "p%" as suspect and build $\mathbf{Z}_4$ given the suspects; 4) fit model [2]; 5) compute full model residuals; 6) repeat steps 3 and 4 to get the final solutions. The full model residual may provide greater accuracy in identifying PT records and reduce the number of false positives because PT is not the only reason a record may be an outlier, relative to its management group. Initial use of steps 1 and 2 may prevent residuals for PT records from being too small due to the PT effect being partitioned into other terms in the model such as **pe** and **a**.

The final aspect of the RPT correction, which requires further consideration, is the variance attributed to the random PT effect. Perhaps it would be possible to estimate this parameter from the data. It is worthwhile to emphasize, however, that the variance for the random PT effect used in this study was arrived at only once, using only a single replicate, in a preliminary analysis; it was not derived separately for each replicate, based on the most favorable results. Thus, simply utilizing a small value, which works well in simulation under a variety of conditions for PT, may be adequate in practice, particularly if the estimated variance does not give good results in simulation.

MIXTURE MODEL

There was little to no effect of the mixture model on either biases (Tables 8 and 9) or ranking (Tables 10 and 11). The reason for lack of effect can be seen in Table 11 which gives the average $\Pr(PT|r_i)$ for records receiving PT. These probabilities were quite low, too low for the mixture model to be effective in reducing bias due to PT or to have much effect on ranking. Improvement in estimation of these probabilities is most likely possible. Calculation of the $\mathbf{X}_2$ probabilities utilized σ_e^2 which, of course, is incorrect. When the true errors (e_i), rather than the residuals, were used to compute the X_2 probabilities, the average $\Pr(PT|e_i)$ was .64, when relative frequency of PT was .05. Of course, true errors cannot be used in practice but a more correct variance for the residuals could be used. An initial attempt to improve the mixture model as a means to correct for PT, therefore, would be to replace σ_e^2 with $Var(r_i)$ in the calculation of $Pr(PT|r_i)$, or at least a better approximation than σ_e^2. It might also be feasible to condition these probabilities on more than just a single record. The obvious first extension would be to utilize all records on cows which have more than one record and relative records could be used as well. It is not clear, however, that this will improve estimation of these probabilities since it is quite possible that all records on a given cow may be inflated by PT and possibly even relatives (e.g., dam, female sibs) have received PT.

The iterative procedure used to calculate the X_2 probabilities was initialized by computing $r_i^* = y - X_1\hat{m} - Z_1\ddot{pe} - Z_2\hat{sh} - Z_3\hat{a}$, where $\hat{m}$, $\ddot{pe}$, $\hat{sh}$, $\hat{a}$ were solutions from model [1], not model [3], and then using r_i^* to compute the initial X_2 matrix. Even though the PT effect would be partly partitioned into the animal and permanent environmental solutions in this initial step, and thereby taken partially out of the residual, the expectation was that the correct partitioning would be achieved over iterations. This expectation, however, may not have been realized. As with the RPT method, it may prove more effective to utilize the management group residual, rather than the full model residual, at least in the initial step. Finally, estimating the PT effects may actually be more effective at reducing bias than using the true values. Though not ideal, low values for $Pr(PT|r_i)$ may be compensated for by overestimates of the PT effects and there is no particular interest in the PT solutions. The price for this, however, may be a negative effect on ranking since overestimates would also affect non-PT records.

Although reductions in bias brought about by the mixture model, as fit in this study, were not large enough, there were several aspects of the results worth noting for future reference. The mixture model may be effective in reducing bias in PTA due to PT, only if p is "relatively high," perhaps 10% or more. As mentioned, the average $Pr(PT|e_i)$ was only .64 when p was .05. Although difficult to draw specific conclusions from Table 10, it is clear that estimation of the X_2 probabilities improves as p increases. One favorable tendency, illustrated in Table 11, was that $Pr(PT|r_i)$ improved with increasing magnitude of PT effect. Furthermore, for the 2263 kg PT effect, the mixture model did reduce bias somewhat. Although the reduction in bias was not large enough, this reduction was brought about without any sacrifice in the mean TA of the top 5%. In fact, mean TA of the

Table 8. Biases in PTA of cows randomly selected for PT.

	PT effect, kg					
	905		1358		2263	
p[1]	Adj	No-adj[2]	Adj	No-adj	Adj	No-adj
.01	69	70	129	130	243	255
.05	116	118	191	200	317	376
.10	155	159	248	263	379	485

[1]Relative frequency of PT in the population.
[2]Adj/No-adj are kg bias in PTA with/without the adjustment.

Table 9. Biases in PTA of elite cows selected for PT.

	PT effect, kg					
	905		1358		2263	
p[1]	Adj	No-adj[2]	Adj	No-adj	Adj	No-adj
.01	75	75	118	120	184	205
.05	75	77	134	143	236	307
.10	194	194	286	292	401	514

[1]Relative frequency of PT in the population.
[2]Adj/No-adj are kg bias in PTA with/without the adjustment.

Table 10. Mean true TA of top five percent.

	PT effect, kg					
	905		1358		2263	
p[1]	Adj	No-adj[2]	Adj	No-adj	Adj	No-adj
.01	1727	1724	1759	1759	1704	1700
.05	1774	1776	1704	1701	1459	1428
.10	1660	1657	1581	1576	1290	1270

[1]Relative frequency of PT in the population.
[2]Adj/No-adj are kg mean TA with/without the adjustment.

Table 11. Mean conditional probability of PT for records that received PT.

	PT effect, kg					
	905		1358		2263	
p[1]	Random	Elite[2]	Random	Elite	Random	Elite
.01	.013	.015	.018	.026	.047	.102
.05	.062	.065	.080	.094	.167	.254
.10	.120	.102	.145	.121	.254	.272

[1]Relative frequency of PT in the population.
[2]Random/Elite are mean probabilities for randomly selected/elite PT cows.

top 5% improved slightly with the adjustment.

One apparent anomaly in the results was that, for a given PT effect, bias (Tables 8 and 9) actually increased as p increased, even though X_2 probabilities improved as p increased. This was due to relationships among animals receiving PT increasing, as p increased. It will be difficult to prevent this confounding in the simulation unless number of sires is arbitrarily increased beyond what is realistic for the actual population.

CONCLUSIONS

Power transformations applied to the phenotypic records, as a method to correct for PT, held the appeal of computational ease and lack of need to identify any particular records as having received PT. Transforming with a power of .1 reduced bias to zero but the effect on ranking was severe and attempts to circumvent this effect were unsuccessful. Thus, the power transformations do not appear to be an acceptable approach to correcting for PT.

The RPT correction does hold promise as a method for reducing bias in PTA due to PT. When PT records are identified, the random PT effect essentially eliminates the bias in PTA caused by PT, given an appropriate variance for the PT effect. The likelihood of identifying PT records depends, in part, on magnitude of the PT effect. Thus, the RPT correction is expected to remove at least the largest biases due to PT. The cost associated with the RPT correction, in terms of mean true TA of the top 10% of cows, appears to be small. Beyond finding a rapid method or an approximation for computing variance of residuals, further research should focus on improving the accuracy of identification, both eliminating false positives which will reduce the potential cost of the method, and increasing the success of identifying PT records which will reduce mean bias.

The mixture model also warrants further investigation as a method to correct for PT. If estimation of the probability of PT for PT records can be improved, the mixture model may be an effective way to reduce bias in PTA, caused by PT, without a concomitant cost in ability to rank animals. The limiting factor for the mixture model will likely be the relative frequency of PT in the population. If this frequency is too low, it appears the mixture model will not be effective in reducing biases due to PT. Utilizing the correct variance for the residuals would be the first step in trying to improve calculation of $Pr(PT|r_i)$ for PT records. Using management group, rather than full model, residuals may also improve these calculations.

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APPENDIX

Derivation of variance of management group residual.

Preliminary results needed in derivation

Let $C = \begin{bmatrix} C_{11} & C_{12} & C_{13} & C_{14} \\ C_{21} & C_{22} & C_{23} & C_{24} \\ C_{31} & C_{32} & C_{33} & C_{34} \\ C_{41} & C_{42} & C_{43} & C_{44} \end{bmatrix}$ be the inverse of the coefficient matrix:

$$W'W = \begin{bmatrix} X'X & X'Z_1 & X'Z_2 & X'Z_3 \\ Z_1'X & Z_1'Z_1 + I\alpha_1 & Z_1'Z_2 & Z_1'Z_3 \\ Z_2'X & Z_2'Z_1 & Z_2'Z_2 + I\alpha_2 & Z_2'Z_3 \\ Z_3'X & Z_3'Z_1 & Z_3'Z_2 & Z_3'Z_3 + A^{-1}\alpha_3 \end{bmatrix}$$

where: α_1 = ratio of error to permanent environmental variance;
α_2 = ratio of error to sire by herd interaction variance; and
α_3 = ratio of error to additive genetic variance.
and X, Z_1, Z_2, Z_3 are as defined for model [1].

Then, by definition of inverse,

$C^*W'W = \begin{bmatrix} I & 0 & 0 & 0 \\ 0 & I & 0 & 0 \\ 0 & 0 & I & 0 \\ 0 & 0 & 0 & I \end{bmatrix}$ which implies:

$C_{11}X'Z_1 + C_{12}(Z_1'Z_1 + I\alpha_1) + C_{13}Z_2'Z_1 + C_{14}Z_3'Z_1 = 0$ (by multiplying row 1, column 2)
$C_{11}X'Z_2 + C_{12}Z_1'Z_2 + C_{13}(Z_2'Z_2 + I\alpha_2) + C_{14}Z_3'Z_2 = 0$ (by multiplying row 1, column 3)
$C_{11}X'Z_3 + C_{12}Z_1'Z_3 + C_{13}Z_2'Z_3 + C_{14}(Z_3'Z_3 + A^{-1}\alpha_3) = 0$ (by multiplying row 1, column 3)

The following result is also used: $Var(\hat{m}) = C_{11}\sigma_e^2$ which is given in Henderson (1).
Now:

$$\begin{aligned} Var(\hat{e}) &= Var(y - X^*\hat{m}) \\ &= Var(y) + Var(X\hat{m}) - Cov(y, \hat{m}')X' - XCov(\hat{m}, y') \\ &= Var(y) + XC_{11}X'\sigma_e^2 - Cov(y, \hat{m}')X' - XCov(\hat{m}, y') \end{aligned}$$

Thus, to show that $Var(\hat{e}) = Var(y) - XC_{11}X'\sigma_e^2$, it need only be shown that $XCov(\hat{m}, y') = XC_{11}X'\sigma_e^2$.

Proof:

Note that $\hat{m}$ = row 1of C times the right-hand sides of the mixed model equations
$= (C_{11}X' + C_{12}Z_1' + C_{13}Z_2' + C_{14}Z_3')y$

$X\mathrm{Cov}(\hat{m}, y') =$

$X\mathrm{Cov}[(C_{11}X' + C_{12}Z_1' + C_{13}Z_2' + C_{14}Z_3')y, y']$

$= X(C_{11}X' + C_{12}Z_1' + C_{13}Z_2' + C_{14}Z_3')\mathrm{Cov}(y, y')$

$= X(C_{11}X' + C_{12}Z_1' + C_{13}Z_2' + C_{14}Z_3')(Z_1Z_1'\sigma_1^2 + Z_2Z_2'\sigma_2^2 + Z_3AZ_3'\sigma_3^2 + I\sigma_e^2)$

$= X(C_{11}X'Z_1 + C_{12}Z_1'Z_1 + C_{13}Z_2'Z_1 + C_{14}Z_3'Z_1)Z_1'\sigma_1^2 +$

$X(C_{11}X'Z_2 + C_{12}Z_1'Z_2 + C_{13}Z_2'Z_2 + C_{14}Z_3'Z_2)Z_2'\sigma_2^2 +$

$X(C_{11}X'Z_3 + C_{12}Z_1'Z_3 + C_{13}Z_2'Z_3 + C_{14}Z_3'Z_3)AZ_3'\sigma_3^2 +$

$X(C_{11}X' + C_{12}Z_1' + C_{13}Z_2' + C_{14}Z_3')\sigma_e^2$

$= -XC_{12}Z_1'\sigma_e^2 - XC_{13}Z_2'\sigma_e^2 - XC_{14}Z_3'\sigma_e^2 + XC_{11}X'\sigma_e^2 + XC_{12}Z_1'\sigma_e^2 + XC_{13}Z_2'\sigma_e^2 +$
$XC_{14}Z_3'\sigma_e^2$

$= XC_{11}X'\sigma_e^2$

GENERAL CONCLUSIONS

Preferential treatment (PT) can cause serious biases in both female and sire predicted transmitting abilities (PTA). Bias increases linearly as magnitude of PT effect increases. For cows, bias also depends on number of records on the cow, whether all or only second and later records have received PT, and whether or not relatives have also received PT. For sires, bias depends largely on the proportion of daughters receiving PT and to a lesser extent on total number of daughters. Bias in sire PTA also depends on distribution of daughters across herds. As more PT daughters occur in a single herd, bias decreases because the management group and sire by herd interaction effects begin to account for more of the PT effect.

Three methods were examined for effectiveness in reducing bias caused by PT: power transformations applied to the phenotypic records, fitting a random PT effect in the model for genetic evaluation for records identified as suspect for PT, and a two-group mixture model. Transforming records with a power of .1 reduced bias to zero but had very adverse effects on ranking. Power transformations cannot be recommended for use in practice as a means to correct for PT in genetic evaluation. The random PT and mixture model approaches both hold promise as a means to correct for PT and warrant further investigation and development.

Further development of the random PT approach should focus on improving the identification step. When PT records are identified, the random PT effect reduces bias to nearly zero, given an appropriate variance for the PT effect. Some address will also need to be given as to what variance to use for the random PT effect because the effectiveness of this approach is sensitive to that variance. It may be adequate, however, to simply use a value that works well in simulation, one that strikes a balance between removing bias caused by PT and has, at most, only a small effect on ranking.

Further development of the mixture model will need to first focus on improving calculation of the conditional probabilities of PT for PT records. Calculation of these probabilities involved the variance of the residuals, which is a function of the inverse of the coefficient matrix of the mixed model equations. As an approximation, the variance of true errors was used in place of the residual variances. Utilizing the correct variance, or at least a better approximation, may be adequate to improve the probability of PT for PT records.

Assuming these probabilities are improved, estimation of the relative frequency of PT in the population, needed to calculate the conditional probabilities of PT for each record, will need to be addressed. Furthermore, it appears the limiting factor of the mixture model will be the (true) relative frequency of PT in the population. Calculation of the conditional probabilities of PT for PT records improved as relative frequency of PT increased from .01 to .10. However, even when true errors were used, the probability of PT was, on average, only .64 for PT records when relative frequency of PT in the population was .05. Some address will also need to be given to the number of PT groups in the mixture model. The "optimum" number of PT groups could be treated as another mixture parameter to be estimated. It would be worthwhile, however, to first test the effectiveness of the two-group model when more than two levels of PT are simulated. The two-group model may prove adequate even when there are more than two levels of PT. This would be ideal in the sense that it would circumvent the need to estimate number of PT groups.

IMAGE EVALUATION TEST TARGET (QA-3)

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